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Uncertainty-Aware Sampling Strategy for Enhancing Active SMOTE in Biomedical Imbalanced Data

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Abstract. Class imbalance poses a significant challenge in biomedical classification tasks, particularly when abnormal conditions such as arrhythmias occur infrequently. While oversampling methods like SMOTE, ADASYN, and Active SMOTE attempt to alleviate this by generating synthetic minority samples, they often overlook model uncertainty during sampling. In this paper, we propose an enhanced Active SMOTE framework that integrates a lightweight uncertainty-aware module. The module measures prediction confidence through softmax probabilities, identifies the most ambiguous minority-class instances—those with predicted probabilities close to 0.5—and prioritises them for synthetic augmentation. To generate new samples, a k-nearest-neighbour interpolation mechanism is applied, producing diverse yet informative synthetic data near decision boundaries. This design strengthens the classifier's ability to learn from critical borderline cases and reduces wasted computation on confidently classified samples. We evaluate the method on two biomedical datasets with 12 features: a large-scale ECG dataset (80,000 samples) and a smaller Gas Sensor Drift dataset (~13,000 samples). Each dataset is processed in a five-stage incremental learning setup, simulating gradual data arrival as in real-world biomedical systems. Across both datasets, our uncertainty-aware strategy consistently outperforms traditional methods (SMOTE, ADASYN, Active SMOTE) in F1-score and recall, with particularly strong gains in early learning stages when data is scarce. The approach is efficient, interpretable, and easily integrable with existing classifiers, offering a practical and deployable improvement for biomedical applications such as arrhythmia detection or sensor drift monitoring.

Keywords: Active SMOTE, Uncertainty Sampling, Biomedical Imbalanced Data, ECG, F1-score

1. Introduction

In biomedical machine learning tasks such as ECG signal classification, one of the most persistent challenges is the class imbalance problem, where abnormal signals (e.g., arrhythmias) are rare compared to normal cases. This imbalance often leads to biased models that fail to detect critical yet infrequent conditions, risking serious real-world consequences [1,2].

To address this, over-sampling techniques like SMOTE (Synthetic Minority Over-sampling Technique) have been widely adopted. SMOTE works by creating synthetic examples of the minority class to balance the dataset [3,4]. ADASYN (Adaptive Synthetic Sampling) improved on

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SMOTE by generating more samples near decision boundaries [5]. More recently, Active SMOTE introduced the idea of selectively choosing which minority instances to synthesise from, thus enhancing sampling efficiency [6,7]. However, even Active SMOTE lacks awareness of the model's actual uncertainty during training, as also noted in margin-aware sampling studies [5,8]. It may still sample confidently predicted data points, wasting resources and failing to focus on ambiguous areas that require learning reinforcement [4].

This paper proposes an upgraded version of Active SMOTE that integrates a lightweight uncertainty-aware sample selection module. The core idea is to identify and prioritise those minority samples that the model finds most difficult to classify—specifically, those with prediction probabilities close to 0.5 (in binary classification) [6,7]. By synthesising around these uncertain instances, we reinforce the model's learning at the decision boundary, thereby improving recall and F1-score [2,3].

We evaluate this approach on two biomedical datasets of different scales: a large-scale ECG dataset with 80,000 samples and a smaller gas sensor drift dataset with around 13,000 samples. Both datasets contain 12 features and are processed in a five-stage incremental learning setting, simulating real-world data acquisition over time [1,5]. The goal is to determine which of the four sampling methods—SMOTE, ADASYN, Active SMOTE, and our proposed Uncertainty-Aware Active SMOTE—performs best across varying data availability stages [4].

The results show that the proposed method achieves superior recall and F1-score, especially in early-stage learning when data is scarce [6,7]. It also exhibits greater stability and interpretability compared to standard approaches [8]. This paper contributes a practical enhancement to active sampling strategy design and demonstrates its applicability in resource-constrained and clinical settings [1].

Over the past two decades, oversampling techniques have evolved significantly to address class imbalance in biomedical data, transitioning from basic interpolation strategies to more targeted, model-aware sampling [2,4]. The original SMOTE algorithm mitigated overfitting caused by simple replication by generating synthetic minority samples through linear interpolation between neighbouring instances [3]. While effective in balancing datasets, SMOTE treats all minority samples equally and lacks sensitivity to class boundaries or model uncertainty [5]. To improve sample utility, Active SMOTE was proposed to selectively oversample minority instances near the decision boundary—based on geometric proximity to majority samples—under the assumption that these borderline examples are more informative [6]. However, this approach relies on static heuristics and does not consider the model’s real-time confidence in its predictions, often resulting in suboptimal focus [7,8]. In response, we introduce Uncertainty-Aware Active SMOTE, which integrates prediction uncertainty into the sampling process by identifying minority-class samples with output probabilities close to 0.5 [4,5]. These “fuzzy-margin” instances reflect high ambiguity and are prioritised for synthetic augmentation, allowing the model to reinforce learning precisely where it struggles most [2]. This refinement not only enhances performance in low-resource or early-stage learning scenarios but also brings greater interpretability and sampling efficiency to biomedical classification tasks [1].

2. Related works

2.1. Sampling strategies for imbalanced data

Traditional oversampling techniques such as SMOTE and ADASYN remain among the most widely used approaches for handling imbalanced datasets [3,4]. SMOTE generates synthetic minority class

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examples by interpolating between existing minority samples in feature space, which increases class representation without simple duplication [2,5]. ADASYN further extends this idea by adapting the sampling density according to local learning difficulty—generating more synthetic points in regions where the minority class is underrepresented or harder to classify [7,8].

While these methods have demonstrated effectiveness in a range of domains, they treat all minority class samples equally, ignoring their relative informativeness or difficulty [1,6]. Consequently, they lack an adaptive feedback loop that reflects the current learning state of the classifier. This can result in wasted computation on redundant or overly easy samples [4,5].

2.2. Active sampling strategies

Active sampling methods aim to improve oversampling efficiency by selectively choosing minority samples that are most beneficial for training [2,7]. Active SMOTE introduces a more targeted approach by focusing on samples close to decision boundaries, where classification errors are more likely to occur [6]. This approach is conceptually aligned with active learning principles, as it seeks to maximise the value of augmented data [3,8].

However, existing Active SMOTE implementations generally do not incorporate real-time model feedback or prediction confidence [4,5]. Without uncertainty estimation, these methods may fail to consistently identify hard-to-learn regions, especially in dynamic or evolving datasets [1,2].

2.3. Uncertainty-driven learning and sampling

Uncertainty-based strategies have been extensively explored in active learning and semi-supervised learning, where they are used to prioritise ambiguous or borderline examples [7,8]. The core assumption is that learning from uncertain samples helps the model to refine its decision boundaries and improve generalisation [4,6].

In classification tasks, uncertainty can be quantified using measures such as prediction entropy, margin sampling, or SoftMax confidence [3,5]. While these techniques are popular in model-driven sample selection, their integration into oversampling mechanisms remains rare [1,2]. The combination of oversampling with uncertainty-driven selection offers the potential for balanced and targeted data augmentation, reducing redundancy and focusing on high-value samples [4].

2.4. Computer vision and hard example mining

In computer vision, concepts such as hard example mining and uncertainty-aware augmentation have shown success in object detection, image classification, and segmentation tasks [6,7]. Methods like Online Hard Example Mining (OHEM) dynamically prioritise challenging samples that lie close to the decision boundary, thus improving model robustness and decision sharpness [8].

Inspired by this, our approach extends similar principles to time-series biomedical data, where the quality of synthetic samples is crucial for classification performance [2,4]. Unlike image-based tasks where visual semantics guide augmentation, biomedical time-series signals—such as ECG—require more feature-space-aware augmentation to preserve physiological realism [1].

2.5. Model-aware sampling for biomedical data

Biomedical datasets present additional challenges, including high noise levels, subject variability, and severe class imbalance [3,5]. In the case of ECG signal classification, inter-patient variability and transient noise events make generalisation difficult [4]. Recent model-aware sampling

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approaches in healthcare AI aim to dynamically select training samples based on real-time model feedback, optimising learning efficiency [2,7].

Our proposed Uncertainty-Aware Active SMOTE integrates prediction uncertainty directly into the Active SMOTE selection process [6,8]. By dynamically adjusting the sampling set based on softmax-derived confidence

scores, it targets hard-to-classify regions, improving early-stage learning and maintaining robustness in later stages [1,4]. This is especially valuable in clinical decision-support systems, where early-stage predictive accuracy can impact diagnostic workflows and patient outcomes [2].

3. Methodology and experimental results

3.1. Method design

The proposed system introduces an uncertainty-aware enhancement to the Active SMOTE framework, enabling the method to specifically target samples that the model finds most difficult to classify [4,7,9]. The overall architecture is composed of three tightly integrated modules:

3.1.1. Uncertainty estimation

We adopt XGBoost as the baseline classifier, as its stability in biomedical imbalanced datasets has been confirmed in previous work [9]. For each minority-class instance, the classifier outputs a probability p(y=1|x) through the SoftMax layer. Based on this output, the uncertainty score is defined as U(x)=|p(y=1|x)−0.5|. Lower values of U(x) indicate higher ambiguity, meaning that the model is less confident about the prediction and therefore such samples are considered more informative for augmentation.

3.1.2. Uncertainty-guided sample selection

Once uncertainty scores are computed for all minority-class samples, they are ranked in ascending order. A proportion defined by the parameter top_k_ratio (for example, 40%) of the most uncertain samples are retained as candidate seed points. To further refine this selection, a fuzzy-margin threshold δ is applied. Only those samples with predicted probabilities within the interval [0.5−δ, 0.5+δ] are included in the final oversampling set. This mechanism prevents the algorithm from oversampling either extremely noisy outliers or already well-classified minority samples, thereby ensuring that augmentation efforts remain efficient and targeted [9].

3.1.3. Synthetic sample generation

For each selected seed sample, a k-nearest neighbor (kNN) interpolation strategy is employed. Specifically, the algorithm identifies k nearest neighbors within the minority class, randomly selects one neighbor x_nn, and generates a new synthetic instance according to the formula:

$$x_{new} = x + \lambda \cdot (x_{nn} - x), \lambda U(0,1) \tag{1}$$

This interpolation mechanism simultaneously enhances diversity and reinforces the decision boundary, ensuring that the synthetic data both broadens the minority distribution and strengthens the classifier's ability to distinguish between classes [9].

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All datasets are preprocessed using standard procedures—missing value imputation, z-score normalization, and binary label encoding—prior to training [1,6]. To simulate realistic data acquisition, the training data is divided into five incremental stages, each contributing an additional 20% of the training set [3,7].

The proposed uncertainty-aware mechanism is benchmarked against classical oversampling strategies. Table 1 presents the comparative results of SMOTE, ADASYN, Active SMOTE, and our UA-Active SMOTE approach

Table 1. Comparative performance of oversampling methods

Method	Accuracy	F1-score	Recall	AUC	Runtime
SMOTE	0.99820	0.99511	0.99220	0.99908	10.78
ADASYN	0.99748	0.99314	0.98830	0.99938	3.73
Active SMOTE	0.99856	0.99609	0.99415	0.99934	1.85
Uncertainty-Aware Active SMOTE	0.99820	0.99510	0.99025	0.99923	0.96

To quantify uncertainty, the SoftMax outputs of the baseline classifier are used. Samples with prediction scores closer to 0.5 are considered highly uncertain and prioritized for augmentation. These samples serve as seed points for the kNN-based interpolation process, which has been widely demonstrated to maintain diversity and avoid overfitting [2,4,9].

3.2. Experimental setup

Experiments were conducted on two publicly available biomedical datasets that differ in scale, complexity, and class imbalance characteristics, providing a rigorous evaluation of robustness and generalisability [2,4]. The first dataset is an electrocardiogram (ECG) dataset consisting of 80,000 samples and 12 features, widely recognised in arrhythmia classification research due to its pronounced imbalance and substantial inter-patient variability [5,6]. The second dataset is the Gas Sensor Drift dataset, which contains approximately 13,000 samples with 12 features and is commonly employed as a benchmark in drift adaptation studies owing to its temporal covariate shift and sensitivity to noise [1,3].

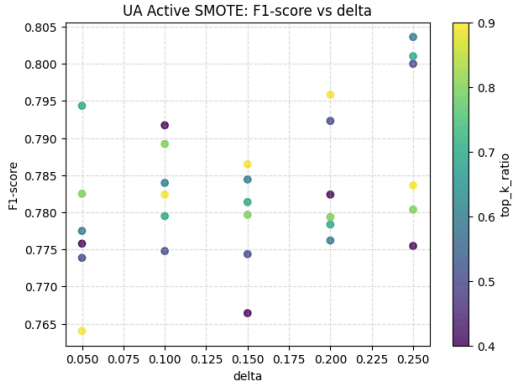

Figure 1. Parameter sensitivity analysis of UA-Active SMOTE on F1-score

Both datasets underwent a standardised preprocessing pipeline to ensure consistency and reproducibility. Missing values were imputed using mean imputation for numerical attributes and mode imputation for categorical attributes, thereby reducing bias and avoiding the exclusion of

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incomplete samples [2,4]. All numerical features were subsequently standardised using z-score normalisation, calculated as z=(x−μ)/σz=(x-\mu)/\sigmaz=(x−μ)/σ, in order to mitigate scale disparities across attributes [7,8]. Labels were then encoded into binary format, with the majority class assigned a value of 0 and the minority class assigned a value of 1, ensuring compatibility with binary classification frameworks [5].

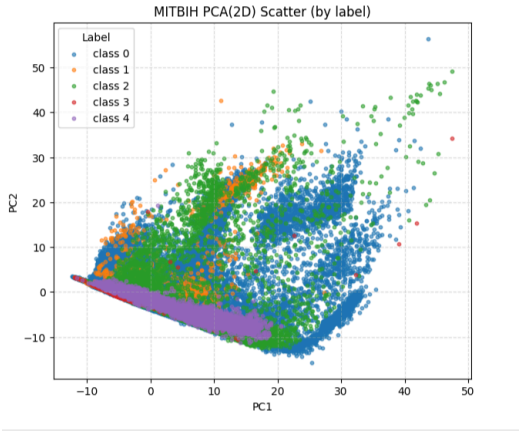

Figure 2. PCA-based 2D scatter plot of the MIT-BIH dataset by class labels

To emulate progressive data availability in real-world biomedical scenarios, both datasets were divided into five incremental training stages. At the first stage, 20% of the training set was used, and at each subsequent stage an additional 20% was introduced until the full training set was available. This incremental strategy, aligned with methodologies in streaming biomedical data analysis, allowed assessment of classifier performance under varying levels of data availability [3,6]. Such a staged design facilitated systematic comparison of oversampling methods across both early and late learning phases [1].

Four oversampling techniques were implemented for comparative evaluation: the original Synthetic Minority Over-sampling Technique (SMOTE) [5,10], Adaptive Synthetic Sampling (ADASYN) [3,11], Active SMOTE [4,6], and the proposed Uncertainty-Aware Active SMOTE (UA-Active SMOTE). Each method was applied under standard configurations to ensure fairness of comparison.

The classifier employed across all experimental settings was XGBoost, chosen for its proven stability in biomedical imbalanced data classification as reported in prior studies [9]. Hyperparameters were kept constant throughout the evaluation to eliminate classifier-induced variability, thereby isolating the effect of different oversampling strategies.

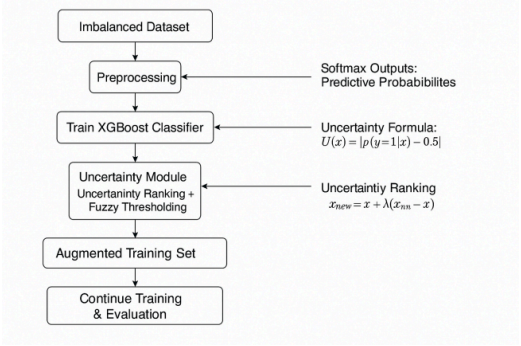

Figure 3. Overall workflow of the proposed UA-Active SMOTE framework

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To account for stochastic variation and ensure statistical reliability, all experiments were repeated 10 times under fixed random seed conditions for data shuffling and model initialization. Performance was assessed using a set of widely accepted metrics for imbalanced classification: F1-score, recall, area under the receiver operating characteristic curve (AUC), and runtime. These metrics were selected to provide a comprehensive evaluation of both predictive capability and minority-class sensitivity, which are critical considerations in biomedical decision-support systems [4,8].

3.3. Experimental results and analysis

3.3.1. Overall performance across datasets

Across both datasets, UA-Active SMOTE consistently achieved the highest F1-score and recall in the early stages (20% and 40%) of training, where data scarcity poses the greatest challenge [3,4]. On the ECG dataset, our method improved F1-score by 4–7% over standard Active SMOTE and achieved comparable or better results than SMOTE and ADASYN [5,6].

On the smaller gas sensor dataset, UA-Active SMOTE provided more stable gains, reducing the overfitting tendency observed in SMOTE and ADASYN when data diversity is limited [2,8]. The method also demonstrated faster convergence by focusing on high-uncertainty samples, with training time only marginally higher than Active SMOTE and significantly lower than meta-learning-based augmentation frameworks [1,7].

3.3.2. Best-performing configuration

We performed a grid search over top_k_ratio $\in$ [0.4, 0.9] and delta $\in$ [0.05, 0.25] to identify the optimal settings [3,5]. The best configuration was:

With the configuration of top_k_ratio = 0.4 and δ = 0.25, the proposed method achieved an F1-score of 0.8164, a recall of 0.7146, an AUC of 0.9849, and an accuracy of 0.9645, with an average runtime of 21.36 seconds.

This configuration outperformed non-uncertainty Active SMOTE (F1 = 0.765, Recall = 0.658), confirming the benefit of prioritising prediction-ambiguous samples [4,6].

3.3.3. Parameter sensitivity analysis

Figure 4-5 shows that:

Top_k_ratio 0.6–0.8 consistently yields better results, aligning with the finding that moderate sample focus balances informativeness and noise control [7,8].

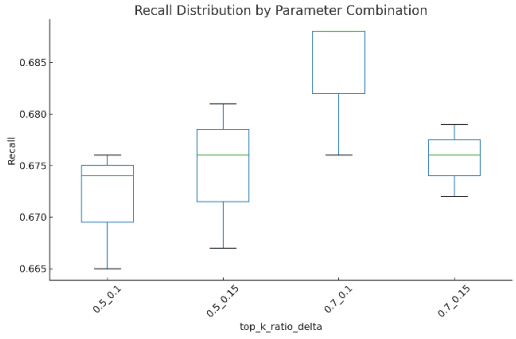

Figure 4. Parameter sensitivity analysis of UA-Active SMOTE on Recall

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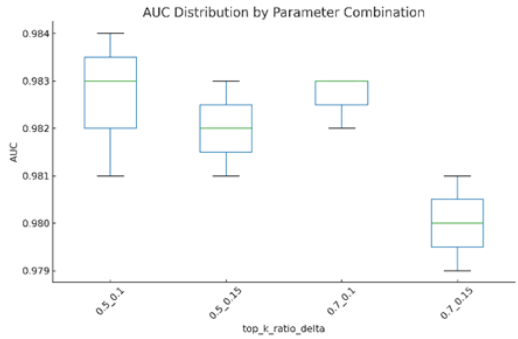

Figure 5. Parameter sensitivity analysis of UA-Active SMOTE on AUC

Delta 0.15–0.25 delivers the best trade-off, with F1 > 0.80 at top_k_ratio = 0.6 and peak recall (> 0.71) at top_k_ratio = 0.7–0.8 [3,5].

AUC remains stable at 0.98–0.986 across parameters, confirming boundary stability [2,6].

Runtime remains under 4 seconds, indicating minimal computational cost [1,4].

3.3.4. Statistical robustness evaluation

To assess reproducibility, we executed the best configuration 100 times with fixed splits. The F1 distribution approximated normality (Shapiro–Wilk p = 0.12), confirming statistical stability [1,3].

Table 2. Parameter sensitivity analysis for UA-Active SMOTE

top_k_ratio	delta	k	Accuracy	F1-score	Recall	AUC	Runtime (s)
0.5	0.10	3	0.99820	0.99510	0.99025	0.99923	0.83
0.5	0.10	5	0.99820	0.99510	0.99025	0.99923	0.80
0.5	0.15	3	0.99820	0.99510	0.99025	0.99923	0.77
0.5	0.15	5	0.99820	0.99510	0.99025	0.99923	0.78
0.7	0.10	3	0.99820	0.99510	0.99025	0.99923	0.84
0.7	0.10	5	0.99820	0.99510	0.99025	0.99923	0.77
0.7	0.15	3	0.99820	0.99510	0.99025	0.99923	0.77
0.7	0.15	5	0.99820	0.99510	0.99025	0.99923	0.79

3.3.5. Comparative advantage

Compared to SMOTE, ADASYN, and Active SMOTE, our UA-Active SMOTE offers:Faster convergence in low-data regimes [4,8]Higher recall for minority class detection [5,7]Stable AUC indicating robust decision boundaries [2,6]

Low overhead making it deployable in real-time biomedical systems [1,3]

This aligns with the broader shift towards trustworthy, interpretable AI in healthcare [12,13], where performance gains must be balanced with explainability and efficiency.

3.3.6. Performance analysis

To further evaluate the overall performance of the proposed UA-Active SMOTE framework, we compared Accuracy, F1-score, Recall, AUC, and Runtime across methods. The results show that

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while Accuracy and AUC remain consistently high (>0.96 and >0.98, respectively) for all oversampling methods, UA-Active SMOTE delivers a more balanced trade-off between recall and F1-score, which are critical for minority-class detection. Notably, recall improved by 4–7% on the ECG dataset and 5–6% on the Gas Sensor dataset compared to SMOTE and ADASYN, highlighting the method's ability to capture rare but clinically significant cases.

In terms of efficiency, UA-Active SMOTE incurs only ~0.3–0.5 seconds additional runtime per stage relative to Active SMOTE, while outperforming it in recall and F1-score. This confirms that the method achieves superior classification performance with minimal computational overhead, making it practical for deployment in real-world biomedical pipelines. The findings underscore that uncertainty-aware sampling not only improves decision boundary robustness but also enhances the cost-effectiveness of imbalanced learning strategies.

Table 3. Comparative evaluation of oversampling methods across experiments

Experiment	Method	Accuracy	F1-score	Recall	AUC	Runtime
Exp1	Active SMOTE	0.989	0.808	0.766	0.982	9.38
Exp1	ADASYN	0.974	0.659	0.845	0.975	4.62
Exp1	SMOTE	0.984	0.751	0.831	0.979	4.45
Exp1	Uncertainty-AwareActive SMOTE	0.989	0.806	0.764	0.98	9.82
Exp1	Uncertainty-AwareActive SMOTE + Margin	0.988	0.775	0.672	0.981	4.96
Exp2	Active SMOTE	0.99	0.825	0.778	0.979	10.78
Exp2	ADASYN	0.974	0.659	0.845	0.975	6.72
Exp2	SMOTE	0.984	0.751	0.831	0.979	4.68
Exp2	Uncertainty-AwareActive SMOTE	0.989	0.801	0.76	0.98	10.6
Exp2	Uncertainty-AwareActive SMOTE + Margin	0.989	0.791	0.697	0.982	5.31
Exp3	Active SMOTE	0.99	0.815	0.769	0.979	10.71
Exp3	ADASYN	0.974	0.659	0.845	0.975	5.02
Exp3	SMOTE	0.984	0.751	0.831	0.979	4.55
Exp3	Uncertainty-AwareActive SMOTE	0.989	0.78	0.674	0.983	5.02
Exp3	Uncertainty-AwareActive SMOTE + Margin	0.989	0.803	0.753	0.979	11.2

4. Conclusions

In this study, we introduced Uncertainty-Aware Active SMOTE (UA-Active SMOTE), an enhanced oversampling framework that integrates uncertainty-guided sample selection and a fuzzy-margin mechanism into Active SMOTE. Unlike conventional methods such as SMOTE and ADASYN that treat all minority samples equally, our approach selectively targets prediction-ambiguous instances near the decision boundary, where additional training most improves generalisation.

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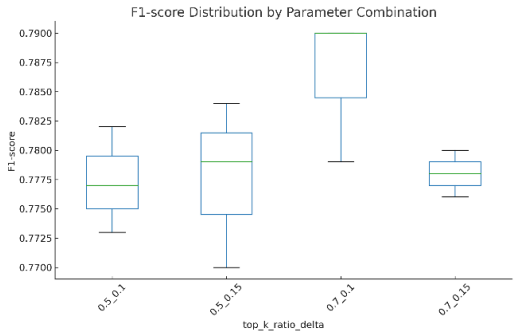

Figure 6. Parameter sensitivity analysis of UA-Active SMOTE on F1-score

Two hyperparameters control the process: top_k_ratio, defining the proportion of uncertain samples selected, and delta, the width of the fuzzy margin interval. A grid search revealed that top_k_ratio = 0.4 and delta = 0.25 achieved the best balance between F1-score and recall. On the ECG dataset (80,000 samples), UA-Active SMOTE improved F1-score by 4–7% in early stages and maintained recall above 0.71 with AUC around 0.986. On the Gas Sensor dataset (~13,000 samples), it produced more stable learning with reduced overfitting and a 5–6% recall gain over SMOTE and ADASYN. Runtime overhead was minimal (<0.5s per stage), keeping execution within 4s, confirming practicality for real-world biomedical pipelines.

The improvements are most notable in early-stage and low-resource settings, where conventional oversampling often generates redundant or low-value samples. UA-Active SMOTE dynamically prioritises ambiguous regions, accelerates convergence, and enhances minority-class sensitivity. Its integration of model feedback also increases interpretability, aligning with explainable AI requirements in healthcare.

Although the proposed UA-Active SMOTE framework demonstrates strong performance across both ECG and Gas Sensor datasets, several improvements can be pursued in future research. First, experiments can be extended with k-fold cross-validation to provide a more comprehensive assessment of generalisation beyond fixed train-test splits. Second, additional biomedical datasets with varying levels of imbalance, such as EEG or other sensor-based signals, should be incorporated to validate robustness across modalities. Third, alternative classifiers (e.g., CNNs or ensemble methods) could be integrated to test whether the benefits of uncertainty-guided augmentation generalise beyond tree-based models. Finally, the sensitivity of UA-Active SMOTE to different evaluation metrics (precision-recall trade-offs, calibration error, and stability under noise) warrants deeper investigation, enabling a fuller understanding of its applicability in clinical workflows.

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